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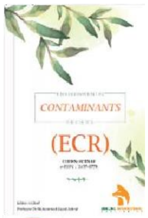

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RESEARCH ARTICLE

SPATIAL MODELING OF AIR POLLUTANT CONCENTRATIONS USING GWR AND ANFIS MODELS IN TEHRAN CITY

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ABSTRACT

Today, air quality is a major subject in city regions that have affected human health, the environment, and the city ecosystem. Therefore, government officials, environmental organizations, health organizations, and city managers often need to model the concentration of air contaminants. This study aimed to compare geographically weighted regression (GWR) modeling and neural network (ANFIS) using Segno and Mamdani rules to spatially predict the concentration density of fNO2, CO, and SO2 pollutant indices. And PM 2.5 for the year 2021 in Tehran. The results of the statistical analysis of Sugeno and Mamdani rules revealed that the (RMSE) in evaluating the ANFIS model with the Mamdani method was 0.895 ppm, and with the Sugno method it was 1.004 ppm, whereas the RMSE in terms of Spatial weighted regression model was obtained on digital model with a height of (12.5 m) and a value of 692.0 ppm. The evaluation results showed that Mamdani and Sugno laws do not have the same and desirable accuracy. For Mamdani law, the RMSE level of PM 2.5 pollutant was (0.71 ppm) and according to Sugno law, this level was obtained for CO pollutant (0.81 ppm). While evaluating the geographically weighted regression model for the four air pollution indices the digital altitude model of (12.5 m) had similar results, which statistically for the digital altitude model of (12.5 m) obtained the RMSE for PM 2.5 (0.82 ppm). The findings of this study demonstrated that the weighted geographic regression model and the ANFI neural network have acceptable functionalities for spatial prediction of air pollutants.

KEYWORDS

Air Pollution, Digital Elevation Model, ANFIS Neural Network, GWR Model, Tehran City

1. INTRODUCTION

Air pollution is specifically referred to as factors that cause discomfort, viruses and human death, and due to the scattering of some substances in the atmosphere will cause dangerous crises for all organisms and the environment (Araujo et al., 2020; García Nieto and Alvarez, 2014; Hu et al., 2019). The World Health Organization states that between 2008 and 2013, urban air pollution worldwide increased by 8% (WHO, 2018). Estimates show that the number of deaths due to air pollution in Iran during the years 1990 to 2013 has increased by about 27 % (Torbatian et al., 2020; Janjani et al., 2020; Jamshidi et al., 2020). As the capital of Iran, as one of the polluted cities in the world, Tehran has faced many health and environmental crises (Torbatian et al., 2020; Janjani et al., 2020; Jamshidi et al., 2020).

Pollution of the city due to land-use changes in recent years, including increasing population density in the city, increasing vehicles, changes in the industry, misplacement of facilities and municipal services, expansion of factories, increased depreciated vehicles, vehicle traffic Personal vehicles and excessive use of fossil fuels (Torbatian et al., 2020; Janjani et al., 2020; Jamshidi et al., 2020). People leaving the countryside and moving to the city are on the rise in the last few years and there are many problems and crises (such as traffic, lack of biodiversity, excessive air pollution, water quality loss, etc) has been created (Ameen and Mourshed, 2019; Silva et al., 2018; Yin, et al., 2014; Zhu, et al., 2019; Leˇsnik et al., 2019; Zhang et al., 2018). With the development of cities, air quality has faced many problems that are worth studying by researchers (Schmitz et al., 2018). All over the world, although much progress has been made, low air quality is also classified as a very severe environmental and health crisis (Schmitz et al., 2018).

Research has shown that PM2.5 pollutants in the atmosphere of developed and developing cities similarly negatively affect the general health of citizens (Gu and Yim, 2016; Landrigan, 2017; Lu et al., 2017a; 2017b; Tu and Tu, 2018). It can be said that if we expose ourselves to air pollutants, in the short term we will see its dangerous effects on health, such as an increased risk of heart disease, respiratory disease, coronary heart disease, and as a result of these cases, we will witness day by day. We are dying and going to the hospital (Tian et al., 2019). However, not only local factors can affect the air quality of a city, but also pollutants that enter a city from far away areas can change the air quality (Seigneur, 2019). Air pollution is considered as a major crisis in the university because it has very worrying effects on the environment and public health, etc. Recent publications in this field also show that pollutants PM2.5, PM10, nitrogen oxides and ozone are known to be the main pollutants (WHO, 2019).

Studies have been done on density modeling of air pollutants done for data from many different parts of the world. In a study of ten concentrations of

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air pollutants (CO_2, NH_3 NO, NO_2, NO_x, O_3, PM1, PM2.5, PM10) on the monster street, a neural network was validated to test their performance (Goulier et al., 2020).A group researchers optimal modeling including spatial, temporal, and decision support systems by multi-criteria decision analysis and neural network for virtual modeling and review of air pollution strategies in Tehran. Ebrahimi and Qaderi a set of fuzzy systems and neural networks to select the appropriate scenario to control SO_2 contamination (Ebrahimi and Qaderi, 2021). In this study, eight variables were evaluated.A group researchers examined the association between air pollutants and pediatric asthma in China.

The results showed that CO, PM10 and O3 pollutants had the greatest impact on the development of asthma. The effects of air pollution on asthma were examined considering its harmful effects (Pfeffer et al., 2020). Exposure to air pollution caused by car traffic and asthma in children ten years and older was suggested and the results showed that NO_2 pollutants play a very bad role in asthma (Lau et al., 2020). Ghanbari and Isazadeh the concentrations of ozone and nitrogen oxide pollutants were modeled annually for Tehran using Sentinel-5 product in the Google Earth system (Ghanbari and Isazadeh, 2021). The results showed that the Aqdasiya station on March 9, 2019, had the highest amount of ozone and nitrous oxide. Showed 0.186 percent.

In order to map particulate matter in the southwest of Iran, conducted a study using linear regression (LR), multiple linear regression (MLR), geographically weighted regression (GWR), and ordinary least square (OLS) (Soleimany et al., 2022). All of the models used revealed practical functionalities in predicting and mapping particles, and GWR revealed the most logical outcomes. The research conducted by to predict PM2.5 pollutant using a hybrid approach of least square support vector machine and optimization algorithms showed that the use of hybrid techniques increases the accuracy of the results (Yang et al., 2022). A group researchers carried out research to review the most widely used methods in spatial prediction of PM2.5 (Anchan et al., 2022). The outcomes of this research were classified into two categories: machine learning and statistical methods.

Furthermore, this research highlighted GWR as one of the most widely used methods in air pollution modelling. A group researchers provided a hybrid model of bi-directional long short-term memory and full ensemble empirical mode decomposition with adaptive noise (CEEMDAN) (BiLSTM) (Jiang et al., 2021). The application of the novel method to forecast the same type of particulate pollution PM10 and heterogeneous gas pollutant O3 demonstrated the method's potent generalizability. The first step was to break down PM2.5 concentrations at various frequencies using CEEMDAN. Following the calculation of each decomposed wave's fuzzy entropy (FE) value, the near waves were joined using K-means clustering to produce the input sequence. Some researchers carried out a spatiotemporal analysis of air pollutants in northeastern Mexico using ENN models (Carmona et al., 2020).

They ensemble various methods of ANN to present a feasible approach for spatial prediction of the air pollution from 2010 to 2014. A group researchers utilized deep learning algorithms, CNNs, and LSTM networks to predict PM2.5 and compared the capability of these methods and highlighted that the CNN approaches have higher accuracy (Carmona et al., 2020). The province of Tehran is the largest city in Iran with a population of 13 million people (Statistics Center of Iran, 2016), it one of the metropolitan cities of the world can be geographically and topographically, and the climatic conditions that have been created for this city there are more than 4 million cars, and 3 million motorcycles, 45% of the total industry, the concentration of 70% of services and 80% of the specialists of this city has become one of the most polluted cities in the world (Tehran Municipality, 2016; Environmental Protection Organization, 2016).

Increasing the concentration of pollutants has become a major challenge for the management of Tehran metropolis. Awareness of the mechanical distribution of air pollutants in this city allows Tehran metropolitan managers to take appropriate measures to reduce the risk of areas and people at risk. Because modeling the dispersion of air pollutant concentrations is one of the most appropriate methods for planning and decision making. Spatial modeling of density concentrations of CO, NO_2, SO_2, PM2.5 pollutants in Tehran for 2021, using ANFIS fuzzy neural network model and geographical weight regression model is the main purpose of this study.

2. Study Area

The city of Tehran is the capital of Iran, which is geographically located in the northern part of the country and has a population of about 8,694 people (Statistics Center of Iran, 2016). The population of this city with the migration of people from the cities around Afghan immigrants for work and education and tourists from all over the country entering this city has caused its population to reach 12.5 million during the day (Hosseini and Shahbazi, 2018). (Figure 1) shows that the city of Tehran has 349 neighborhoods (Heger and Sarraf, 2018). The topographic features of the city and the location of the city among the Alborz Mountain range cause the confinement of polluted air in the city (Heger and Sarraf, 2018). Table 1. Shows the climatic data and characteristics of Tehran collected from the Synoptic Geophysical Meteorological Station in 2021 (TMMA, 2020).

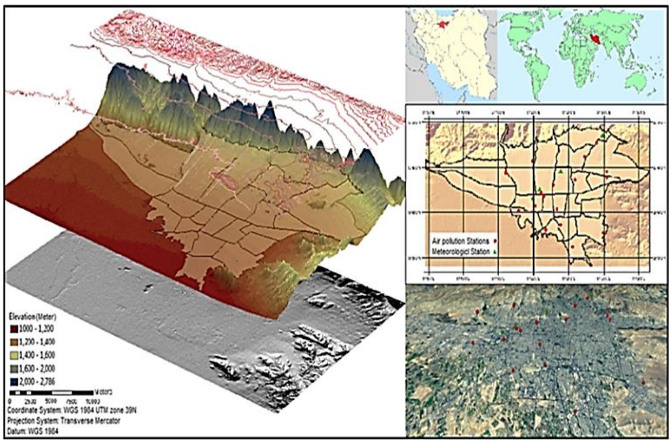

Figure 1: The geographic location of the study region and spatial distribution of the available air pollution monitoring stations.

Table 1: Summary of Tehran Attributes (Tehran Province Meteorological, 2020; Tehran Annual Air, 2018; Tehran Municipality Information, 2020).

Land			Mean temperature				
Area	Elevation	Population	Annual	Spring	Summer	Autumn	Winter
KM^2	m	Million	C^o				
615	900 - 1800	8.8	17.2	19.3	29	13.3	7
Precipitation			**Wind**			**Air Pollution**	
Gross	Pure	Moisture	Prevailing Direction	Maximum speed	Average speed	organization	original
mm		%	$m\ s^{-1}$			..	$\mu g\text{-}m^3$
424	328	24 - 65	West to east	22	2	AQCC	PM

3. Materials and Methods

In this paper, 4 air pollution concentration indices (CO, NO_2, SO_2, PM2.5) for year 2021, from 18 air pollution monitoring stations that were to be used in different areas of Tehran. Air pollution control stations, which are under the supervision of the Environmental Protection Organization and the Air Quality Control Company (AQCC), affiliated to the Tehran Municipality, in addition to air quality measurement, this organization simultaneously monitors meteorological characteristics (https://translate.google.com/). The second data used in this study is the use of digital elevation model maps (12.5 m) in Tehran, which was obtained from the site (https://search.asf.alaska.edu/). 4 indices of air pollutant concentrations are shown in Table 2. For 18 stations. In order to model the spatial density of four air pollution concentration indices, ANFIS neural-fuzzy network model and GWR model in the form of two different models have been used.

In ANFIS neural-fuzzy network model, 4 air pollution concentration indices were obtained for 18 air pollution monitoring stations and an area was considered for each station located in different areas in Tehran and for training the network from the available data in the area. Each station was used. For each area of the station, fuzzy rules (Sugno and Mamdani) were extracted and applied to each pixel of that area, and according to that, the amount of spatial density, four indices of air pollutant concentration were modeled. In the GWR model, 4 air pollution indicators were entered into the software for reverse weighting (IDW) interpolation zoning. Then, the digital elevation model map (12.5 m) along with the zoned maps of the four air pollutant concentration indices became a feature to enter the model in the context description table called weight, the value of which is based on altitude defined. The higher the station, the more weight was assigned to it. The flowchart research is presented in (Figure 2).

Table 2: Air pollutant concentration data for 18 air quality monitoring stations in Tehran (http://airnow.tehran.ir/).

Row	Name	Co	No2	So2	PM2.5
1	Mahallati Highway - Region 14	1.66	45.18	6.96	45.5
2	Aqdasiya - Region 1	2.72	45.59	0	0
3	Ponak	2.29	49.12	3.38	2.3
4	Pirozy- Region 13	1.92	57.99	6.76	3.5
5	Tarbiat modares - Region 6	1.67	49.2	5.61	45.45
6	Stad bohran - Region 7	2.1	52.71	4.09	34.23
7	Shad Abad - Region 18	2.13	45.69	7.96	63.13
8	Sharif - Region 2	1.63	59.19	7.05	34.16
9	Ray City - Region 2	2.26	41.74	5.41	14.12
10	Municipality - Region 16	2.28	0	0	45.5
11	Municipality - Region 19	3.12	47.17	6.25	21.45
12	Municipality - Region 21	1.95	0	7.15	17.97
13	Municipality - Region 2	1.72	48.61	8.53	0
14	Municipality - Region 22	3.42	0	5.18	0
15	Sadr - Region 3	1.86	77.18	5.73	39.67
16	Golbarg - Region 8	1.54	57.23	3.45	33.67
17	Masoudiyah - Region 15	1.54	84.38	2.79	49.27
18	F Atah Square - Region 9	2.31	44.66	6.78	21.28

3.1 Geographically Weighted Regression (GWR Model)

Geographic weighted regression analysis is mainly used to examine the relationship between variables (Gilbert and Chakraborty, 2010). When the relationship between a dependent variable is fixed, it means that one or more independent variables can examine the statistical relationships between the dependent and independent variables with only one equation (Gilbert and Chakraborty, 2010; Fotheringham et al., 2002; Wang et al., 2010). The GWR model examines and evaluates point-shaped variables by means of ordinary least squares with local weighting, respectively (Hu et al., 2012). These models are similar to global regression models and variables with different geographical locations (Hu et al., 2012). GWR by Eq. (1):

$$y_i = \beta01 + \beta1ix_{1i} + \beta2ix_{2i} + \cdots + \beta knXkn + \delta i \quad (1)$$

In this equation, β is the estimated parameter vector, X matrix is the independent variables, and Y is the observed values' vectors.

3.2 ANFIS Algorithm

The ANFIS learning algorithm was first developed (Jang et al., 1997). ANFIS, by means of a feed network, can be used to optimize the variables of a fuzzy system in order to obtain accurate results (Matlab, 2018). The ANFIS algorithm has two modes, one is the initial part and the other is the inference, which are connected by a network called fuzzy rules (Matlab, 2018). Fuzzy inference has three main parts: (I) fuzzy rule (if and then), (II) database (membership functions follow fuzzy rules) (Matlab, 2018). In the law f (x, y) as a polynomial the name of the created law is Sugeno Fuzzy (Guneri et al., 2011). The ANFIS algorithm has five layers, the first layer of which is connected to the fuzzy model and is calculated from Eq. (2): (Wei et al., 2007).

$$O_i^1 = \mu_{Ai}(\mathrm{x}) \quad (2)$$

Where i and Ai as variables, x constitutes the input nodes, O_i^1 as a function of Ai membership. The second lazy efficiency of the "AND" execution algorithm is that this layer itself has loop layers that are multiplied by the input layer but its output is calculated by Eq. (3):

$$W_i = \mu_{Ai}(x) * \mu_{Bi} = 1.2 \quad (3)$$

The normalization function is considered as the third layer in which the sum of the means generated using the rule ist for each node and is calculated using Eq. (4):

$$\overline{W\iota} = \frac{Wi}{W1+W2}\ i = 1.2 \quad (4)$$

Fuzzy rules are used in layer four, where node i is a square node that is computed through Eq. (5):

$$O_i^4 = \overline{W\iota}\, f_i = \overline{W\iota}\ (Pi^X + qi^y + r)i \quad (5)$$

Where wi the third layer output qi, pi, and ri variables are considered as the final parameters (Guneri et al., 2011). The fifth layer consists in which no fuzzification takes place, whereby all input neurons are used to calculate a node as output and are calculated through Eq. (6):

$$O_i^5 = \sum_i \overline{W\iota}\, f_i = \frac{\sum_i \overline{W\iota}\, f_i}{\sum_i wi} \quad (6)$$

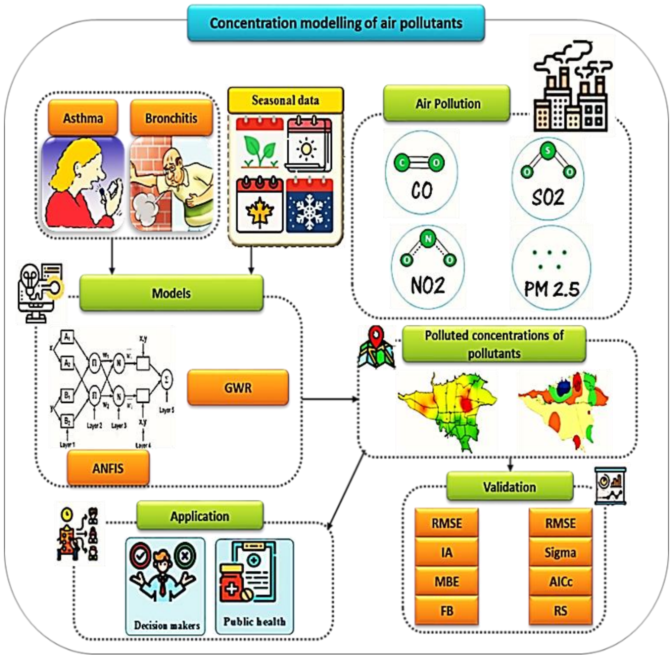

Figure 2: Research flowchart.

4. Results and Discussion

4.1 Training and Testing of Mamdani and Sugno Anfis Networks

In the current study, to train ANFIS Mamdani neural network, the points created in the area of each station were used separately. To do this, each data model was divided into three categories training data (50% data), check data (30% data), and control data (20% data). In ANFIS neural network, training was used in two methods of error propagation and the combined method, error propagation, and least squares. To create the basic rules, two methods of dividing the entrance and exit space and decreasing clustering were used. In the first method, the number of membership functions and their type for four air pollutant indicators Co, No2, So2, and PM 2.5 was obtained from the correct method and error. The results showed that by considering the two membership functions for the four air pollution indices, the use of the Gaussian function produces the best results. In decreasing clustering, the effective distance was considered 0.55. As a result, the Genghis function was used to generate the rules, resulting in fuzzy Sugeno and Mamdani rules for use in this network. Many past studies have consistently used the ANFIS algorithm (Golchoubian et al., 2012; Pouretedal et al., 2018).

4.2 Fuzzy Rules Creating and Examining ANFIS Sugno and Memdani

Mamdani law was used with descending clustering method and bell input and trapezoid output membership functions. But Surgeon's law used reduction clustering methods and the educational membership function

using the combined method and post-error training and chose the method that produces the best results for the four air pollution indicators and gives the best answer. Table 3 and 4. The values of RMSE, AI, MBE, and FB for the selected methods four air pollution indicators of 18 stations in two methods M-ANFIS (Mamdani) and S-ANFIS (Sugno) to display the tested data to the work went. The results of this article are consistent with the research findings (Shahbazi et al., 2013; Amirkhani et al., 2015; Kaboudvandpour et al., 2015; Zande Bodi et al., 2017).

Table 3: Accuracy and Methods Selected by Mamdani Law for CO, NO2, SO2 and PM 2.5 Pollutants.

Pollutant Indicators	CO	NO2	SO2	PM 2.5
Method	Mandel-bell-trap	Sub-gauss-trap	Sub-gauss-gauss	Sub-gauss-gauss
RMSE (ppm)	0.62	0.59	0.67	0.71
IA	0.334	0.450	0.530	0.609
FB	0.053	0.098	0.053	0.028
MBE (ppm)	0.384	0.752	0.653	0.832

Note: Mandel Creation of law by dividing the entrance and exit space, Bell Trap membership function, Trap function Trapezoidal membership function, Sub Create law by subtraction method, Gauss Gaussian membership function.

Using the ANFIS neural network model in (Figure 3), the results of the above four pollutant concentrations for 2021 show that the concentration of Co pollutants for sensitive unhealthy groups in the northwestern part of Tehran is much higher than other areas. While in terms of being healthy in the northeastern and southeastern parts of Tehran is free of concentrations of Co pollutants. Pollution concentration of No2, in terms of unhealthiness is higher in the city center, southeast and southwest. The above concentrations of the above pollutants are unhealthy for more sensitive groups in the southern part of Tehran. However, the concentration of SO2 in terms of unhealthiness is slightly higher in the northern part of the city and the concentration of this pollutant has increased in the central and northeastern parts, so that in the southwestern parts, the level of this indicator of the above pollutant can be seen. PM 2.5 pollutant is one of the most common pollutants in Tehran.

Table 4: Accuracy and Methods Selected by Sugno Law For CO, NO2, SO2 and PM 2.5 Pollutants.

Pollutant indicators	CO	NO2	SO2	PM 2.5
Method	Hyb - Sub	BP - Sub	BP - Sub	Hyb - Sub
RMSE (ppm)	0.83	0.72	0.53	0.52
IA	0.0795	0.678	- 0.245	0.762
FB	0.332	0.298	0.361	0.571
MBE (ppm)	0.383	- 1.32	0.131	0.631

Note: Hyb training using the hybrid method, Sub creating the law through reductive clustering, BP training using the error post-propagation method.

This pollutant imposes many life threats to humans and nature every year. The concentration of this pollutant using ANFIS neural network indicates that the northwest of Tehran is in a critical and dangerous situation in terms of air pollution, while the level of this indicator in the same part of the city is unhealthy for several areas of Tehran has created. Pollutant (PM2.5) among the above three pollutants as one of the most dangerous air pollutants in Tehran in the northwestern parts of the country for 2021. The results of previous research by showed that the majority of Su, Shanghai, Anhui, Hubei and Nan regions have high concentrations (Lee and Sun, 2017; Lu et al., 2017a; Song et al., 2017; Wang et al., 2017). PM 2.5, while the Qinghai Plateau in southeastern China has the lowest PM2.5.

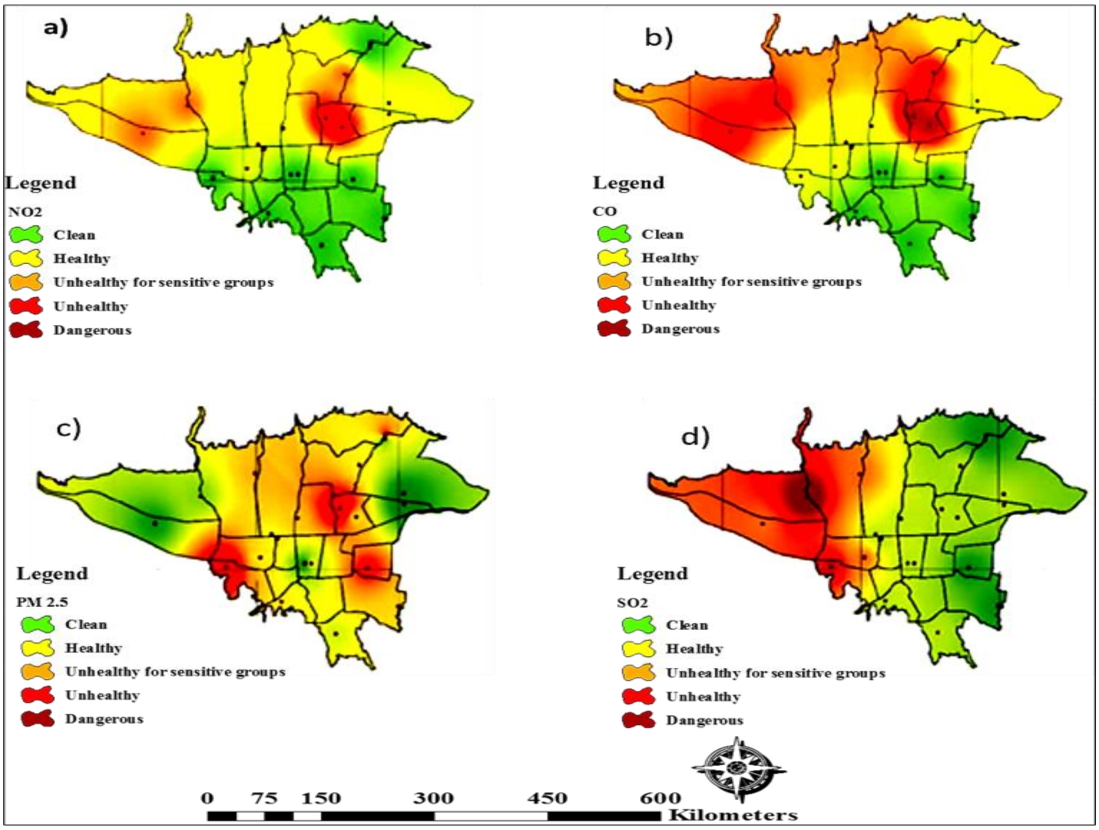

Figure 3: Modeling of four air pollutant concentration indices using ANFIS model (a, b, c, d).

4.3 Effects of Air Pollutant Fluctuations

Evaluation of the correlation between the amount of air pollution in Tehran in 2021 showed a strong dependence on the amount of traffic. While this correlation between the average annual amounts of air pollutants in Tehran and traffic in 22 areas of Tehran is not significant. The results related to the modeling performance temporarily and spatially are shown in (Figure 4). All independent variables used in this modeling have an acceptable level of significance ($p < 0.001$) meaning that all parameters used in this modeling will help to improve the estimation of pollutant concentrations in this study. The model is developed and the amount of R^2 for pollutant concentrations is 0.8195. While this amount for the existing traffic, which is the most important cause of air pollution in Tehran, showed the number 0.67792. To determine the relationship between air pollutants and traffic, the correlation between these two cases was calculated and a strong correlation with a value of 0.7768 showed that this correlation between air pollutants and traffic in the 22 districts of Tehran for 2021 is very significant (Figure 4)

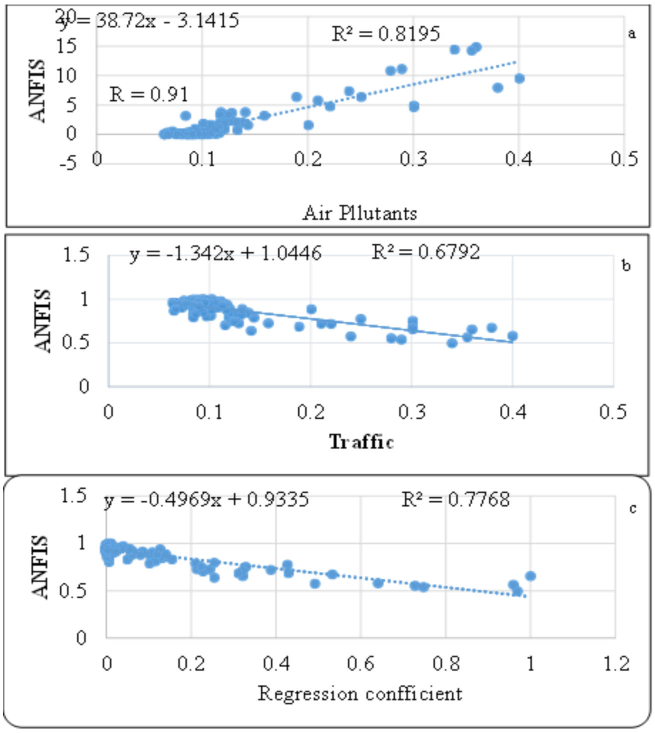

Figure 4: Comparison of air pollutant concentrations with traffic and regression coefficient between them (a, b, c).

4.4 Assessing The Accuracy of Geographic Weighted Regression Model

In this paper, four main air pollutants in Tehran including CO, SO2, NO2 and PM 2.5 were used to implement the geographical weighted regression model along with a digital elevation model map (12.5 m). The value of R2 showed that the good fit of the model is excellent, meaning that the predicted parameters show 82% of the variance for the concentrations of PM 2.5 and CO pollutants. Also, the remaining squares, AICc and RMSE of the model are somewhat small, indicating that the GWR model works well in modeling the concentration of alloys. Findings and validation of the GWR model for the four air pollution indicators are presented in Table 5. In a previous study, used ground data, remote sensing, air quality data, and geographic input to predict PM 2.5 in the Pearl Delta region. The amount of R2 obtained from their results was 0.676 and was smaller compared to the results of the present paper. Certainly, the difference in model performance in previous studies can be related to predictive parameters. A group researchers focused primarily on the effects of meteorological parameters (Song et al., 2014).

Table 5: Results Obtained from The Weighted Geographical Regression Model of NO2, CO, SO2 and PM 2.5 Pollutants on A Digital Model Elevation of 12.5 M.

Pollutant Indicators	RMSE (ppm)	AICc	Sigma	Residual Squares
NO2	0.64	506.06	0.733	78.60
CO	0.70	420.20	0.680	92.27
SO2	0.56	441.81	0.680	82.45
PM 2.5	0.82	624.92	0.859	96.10

In (Figure 5) PM 2.5 pollution index is known as one of the main air pollutants in Tehran and this pollution index has destructive effects on human health and air pollution modeling can help managers to manage and identify polluted areas and consequently take appropriate measures to help reduce the risk. The amount of four pollutant indicators on the digital model map of 12.5m height has been very different from each other. The amount of CO pollutants on the digital elevation map was 12.5m more in the northern and southern parts of Tehran. While the amount of NO2 pollutant on the above map is more in the northern part of the city (Ghiyas et al., 2009; Thorkashvand et al., 2017). However, the amount of SO2 pollution in the northern part of the city has led to an unfavorable situation, but the amount of PM 2.5 pollution in the northeastern and northern parts of Tehran has created a critical and dangerous situation for these areas of the city. The geographical weighted regression model has modeled only CO and PM 2.5 pollutants on the digital model of 12.5m altitude among the above four pollutant indices in terms of being dangerous for the northern regions of Tehran.

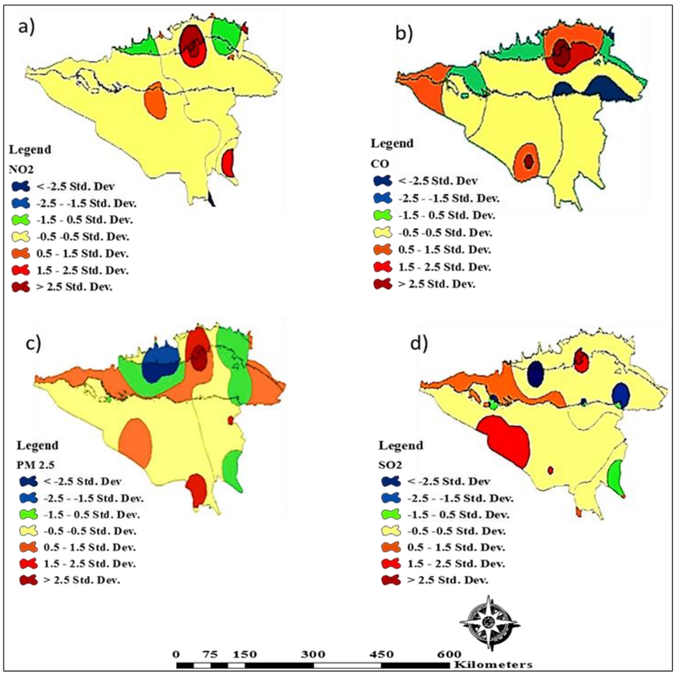

Figure 5: Output of weighted geographical regression model of air pollutant on digital model height 12.5 m (a, b, c, d).

5. Conclusions

Air pollutants (CO, NO2, SO2, and PM2.5) are the main air pollutants in Tehran and have a devastating effect on citizens' health in the short term. Modeling the concentration of air pollutants can help managers and urban planners to manage and identify areas with higher concentrations of pollutants and, consequently, to take appropriate measures to reduce risk and crisis. The aim of this paper was to compare GWR and ANFIS models to model the concentration of air pollutants such as No2, CO, SO2 and PM 2.5. Shows the results obtained from the ANFIS neural network method. The model in 2021 can provide a favorable result ratio to the geographical weighted regression model for four pollutant indices (CO, NO2, SO2, and PM2.5). To teach the ANFIS neural network, Mamdani and Sugno rules governing 18 air pollution monitoring stations were used for four pollution indicators.

Therefore, Segno and Mamdani rules were used in order to create appropriate results for each air pollution control station in Tehran. The results obtained from the ANFIS neural network method based on Mamdani and Sugno rules showed that both methods had almost the same accuracy. While the geographical weighted regression model was obtained on the digital model of (12.5m) height for four air pollution indicators. The results obtained from the ANFIS neural network method based on Mamdani and Sugno rules showed that both methods had almost the same accuracy. While the geographical weighted regression model was obtained on the digital model of (12.5m) altitude for four air pollution indicators.

The results of statistical evaluation of Sugeno and Mamdani rules showed that the (RMSE) in evaluating the ANFIS model with the Mamdani method was 0.895 ppm, and with the Sugno method it was 1.004 ppm, while the RMSE in terms of Spatial weighted regression model was obtained on digital model with a height of (12.5 m) and a value of 692.0 ppm. The results of previous research show that the results of previous research show that examined the concentration of PM2.5 in Tehran. ANFIS neural network and weighted geographic regression models understand that can be easy and usable for environmentalists in urban management in terms of environmental and density measurement overcoming air pollutants.

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